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The impact of currency movements on asset value correlations



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ABSTRACT

This paper looks at the asset correlation bias resulting from firms' assets and liabilities being denominated in different currencies. It focuses on the time-variation in the bias and on the dependency of the bias on currency movements. Overall, we find that the asset correlation bias for the average pair of firms in the Dow Jones Industrial Average index is significant. The bias fluctuates widely, however, and it has turned negative for shorter periods. The policy implication of the paper is that by ignoring the exchange rate component when computing portfolio credit risk one may materially underestimate the actual risk.

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1. Introduction

For the average bank, the risk category that is the most important to manage accurately is credit risk. In order to monitor this risk the typical bank puts much effort into assessing the likelihood that its counterparties will not honor their future contractual obligations. For corporate counterparties (firms) this risk is often estimated using quantitative models, such as the [Merton \(1974\)](#) model. In

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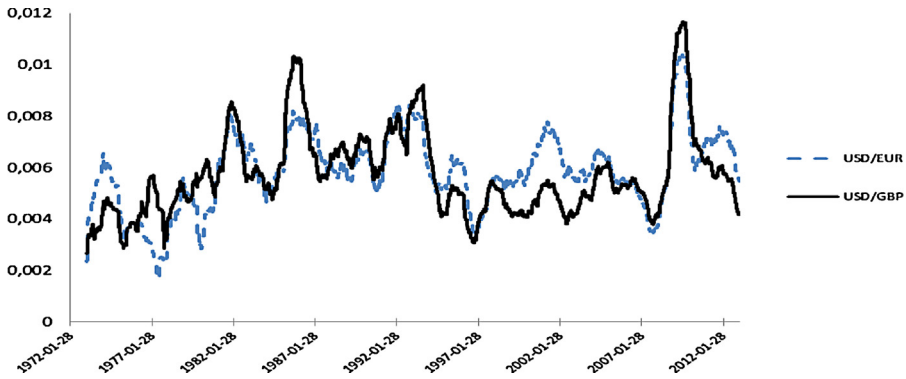


Fig. 1. The volatility of the two USD exchange rates USD/EUR and USD/GBP from 1973 to 2013.

these models the main focus is on the firm's assets and on the likelihood that the market value of these assets falls below the value of the firm's debt at some point in the future. Since banks rarely, or never, lend to one single firm but to a large number of firms, the banks spend much time and money on estimating how the credit risk of one borrower affects the credit risk of other borrowers. This "portfolio perspective" to credit risk modeling requires quantitative estimates of credit risk dependencies and the most commonly used proxy for this dependency is the, so-called, asset correlation.

The asset correlation is simply the correlation between two borrowing firms' asset values and the higher this correlation is the larger the credit risk is when lending to both firms simultaneously. One complication that arises when focusing on correlations between asset values is that asset values are not observable. While the value of a firm's equity is instantaneously available to everyone through the stock market, the asset value is not. Instead, asset values have to be estimated using models, for instance the above-mentioned [Merton \(1974\)](#) model.

In this paper we focus on another important issue when assessing firms' credit risk; namely the risk that currency movements affect the value of the firms' assets. This risk appears when firms have some, or all, of its assets denominated in another currency than its debt. Not only does this currency mismatch affect the likelihood that the firm will default, due to the additional layer of exchange rate risk put on top of the original credit risk, but it also affects the default dependency, i.e. the asset correlation, amongst firms. If the firms have significant portions of their assets denominated in a foreign currency, these firms' asset correlation will typically be biased upwards. As will be shown below, the bias increases not only with the amount of assets held abroad but also with the volatility of the exchange rate as well as with the correlation between the assets and the exchange rate. Now, the volatility of many of the major exchange rates has increased over time and two examples are shown in [Fig. 1](#). This, plus the widespread "risk-on, risk-off" mentality among investors as of lately, with an associated hike in most financial correlations, is likely to have increased the economic significance of the bias.

The first study to acknowledge the issue of currency risk in credit risk modeling is [Tasche \(2007\)](#). While [Tasche \(2007\)](#) derives an analytical relationship that has to hold between asset correlations with and without currency risk he presents no empirical results and does not estimate the actual real-life size of the currency-risk-induced asset correlation bias. To assess the economic importance of the bias, [Byström \(2013\)](#) builds on the theoretical findings in [Tasche \(2007\)](#) and empirically estimates the asset correlation bias for a sample of US firms in different industrial sectors. [Byström \(2013\)](#) finds the bias to be positive and large enough to potentially result in a significant underestimation of actual portfolio credit risk.

In this article we focus on the exchange rate and on how the time-series behavior of the exchange rate affects the asset correlation bias. Particular emphasis is put on the time-variation of the bias, and the fluctuations of the empirically estimated asset correlation bias are compared to the theoretically predicted relationship between the bias and the exchange rate movements. The main finding is that

the asset correlation bias varies significantly over time and that the bias, contrary to the findings in Byström (2013), sometimes is negative for the average firm-pair in the Dow Jones Industrial Average index (DJIA). At least some of this bias time-variation is caused by changes in the volatility of the exchange rate as well as by changes in the correlation of the exchange rate with the firms' asset values; i.e. by changes in the currency dynamics. The empirically observed bias variation is shown to be consistent with the analytically expected sensitivity of the bias to changes in exchange rate-volatility and -correlations.

The policy implication of the paper is clear and simple; ignoring the exchange rate component when computing portfolio credit risk can lead to a significant underestimation of the actual risk. At a time of a heightened risk of significant exchange rate movements, perhaps caused by a euro-area breakup or widespread competitive devaluations, this is more important than ever.

In Section 2 we briefly discuss how exchange rate risk affects the estimation of asset correlations. Section 3 discusses the setup of the study as well as the data, and Section 4 presents the empirical results. Section 5 concludes the paper.

2. The asset correlation bias

Tasche (2007) shows that if borrowing firms hold assets and liabilities in different currencies then the asset correlation estimates among these firms are biased. The additional exchange rate dynamics and its interaction with the asset value dynamics is the cause of this bias and Tasche (2007) demonstrates how to calculate the bias under the assumption that both asset value- and exchange rate movements follow geometric Brownian motions. If r_i is the correlation between these two processes, i.e. the correlation between the exchange rate changes and the asset value changes of borrower i , if σ_i is the volatility of the asset value changes of borrower i and if τ is the volatility of the exchange rate changes, then the relationship between ρ^* and ρ , i.e. the asset correlation with and without a currency mismatch between assets and liabilities, is

$$\rho^* = a + b\rho \quad (1)$$

where the intercept, a , and the slope, b , are, respectively,

$$a = \frac{(r_1\tau/\sigma_1) + (r_2\tau/\sigma_2) + (\tau^2/(\sigma_1\sigma_2))}{\sqrt{(\tau^2/\sigma_1^2) + 1 + ((2r_1\tau)/\sigma_1)}\sqrt{(\tau^2/\sigma_2^2) + 1 + ((2r_2\tau)/\sigma_2)}}$$

and

$$b = \frac{1}{\sqrt{(\tau^2/\sigma_1^2) + 1 + ((2r_1\tau)/\sigma_1)}\sqrt{(\tau^2/\sigma_2^2) + 1 + ((2r_2\tau)/\sigma_2)}}.$$

Here, we use the alternative presentation of the relationship suggested by Byström (2013) rather than the original presentation in Tasche (2007) to emphasize the linear nature of the link between ρ^* and ρ .

3. Data and empirical setup

In order to compute the asset correlation bias, both volatility- and correlation-estimates (σ_i and r_i) involving the non-observable asset value process are required. Tasche (2007) never actually empirically estimates the bias and Byström (2013) uses a credit derivatives based method suggested in Byström (2011) to back out the required time series of asset values. An attractive feature of the Byström (2011) method is that it relies on two separate markets, i.e. the stock market and the credit derivatives market (both being mature and efficient) to get the market value of the firm's entire capital structure. The method is also fairly free of assumptions and simplifications. Here, however, we have instead chosen to use the well-known Merton approach where the asset values are backed out from stock prices and balance sheet data using the Black–Scholes option pricing framework (Merton, 1974). The reason for this choice is threefold. First, this choice will reveal whether the significant bias found in Byström (2013) is merely a result of the way asset correlations are calculated. Second, the Merton approach is

applicable also to firms without traded credit default swaps, i.e. a much larger range of firms can be covered, and, third, the Merton approach is the most widely used method of estimating time-varying asset values and it is therefore a natural choice in this study where the focus is on the time-variation of the asset correlation bias.

The Merton model recognizes that a firm's equity is equivalent to a long position in a call option on the firm's assets with strike price equal to the firm's debt level. As a result, the equity value is expressed as

$$V_E = V_A N(d_1) - e^{-r_f(T-t)} D N(d_2) \quad (2)$$

where V_E , the market value of the firm's equity; V_A , the market value of the firm's assets; D , the firm's debt level (all the debt is homogeneous); $T - t$, the time to maturity of all the firm's debt; r_f , the risk-free interest rate,

$$d_1 = \frac{\ln((V_A)/D) + (r_f + (1/2)\sigma_A^2)(T - t)}{\sigma_A \sqrt{T - t}}$$

$$d_2 = d_1 - \sigma_A \sqrt{T - t}$$

$N(\cdot)$, the cumulative normal distribution

Itô-calculus gives us a second equation, $\sigma_E = (V_A/V_E)N(d_1)\sigma_A$, and from these two equations we can back out V_A , the asset value (Crosbie and Bohn, 2003; Hull et al., 2005). In this study we rely on daily stock price data and, consequently, back out daily asset values/returns that are used to calculate daily (historical) asset volatilities and -correlations. The exchange rate changes, and all the volatilities and correlations required for the calculation of the bias, are also computed using daily data. The risk-free interest rate is proxied by the 3-month US Treasury Bill rate and the default-triggering debt level is set equal to the firm's total debt for non-financial firms and half of the total debt for financial firms. The rationale behind this choice is that financial firms differ from non-financial firms by being much more leveraged. However, the government often supports financial firms in times of crisis, and, as mentioned by (CreditGrades, 2002), this makes financial firms' "effective leverage ratio lower than that implied by standard debt-per-share calculations". CreditGrades (2002) gives no information on how much lower this "effective leverage ratio" should be and, as a result, we calculate effective debt levels for financial firms by simply multiplying the actual debt levels by a half. This choice also shares similarities with the way Moody's KMV chooses the default point in its KMV model as the sum of the short-term debt and half the value of the long-term debt (Crosbie and Bohn, 2003). Finally, the debt level is updated on a daily basis through a linear interpolation between the debt levels at the start and the end of the sample. The stock return volatility is calculated as the 250-day trailing historical standard deviation. All the data is downloaded from Datastream except the debt levels that are downloaded through the A. Damodaran website (<http://pages.stern.nyu.edu/~adamodar/>).

Our study focuses on the 30 firms in the Dow Jones Industrial Average index (DJIA) and the time-period is January 3, 2000 to January 29, 2013. The currencies that we choose for the (hypothetical) currency exposure of the DJIA-firms are the euro (EUR), the British pound (GBP), the Japanese yen (JPY), the Chinese renminbi (CNY), the Argentine peso (ARS) and the US dollar index (USDX). Although similar to the setup in Byström (2013), the current paper differs from that paper in important ways. In addition to the current paper's focus on the exchange rate dynamic's effect on the asset correlation bias, the paper differs from Byström (2013) in the following ways; (i) in looking at the time-variation of the bias, (ii) in the way asset values are estimated (using the Merton (1974) approach instead of the Byström (2011) approach), (iii) in the much larger number of estimated asset correlations (435 compared to 50), (iv) in the selection of firms, (v) in the slightly extended time-period and (vi) in the use of a slightly different set of currencies.

4. Results and analysis

This section is divided into two parts; first, we look at the sensitivity of the currency-risk-induced asset correlation bias to the behavior of the exchange rate using "semi-analytical" relationships, and,

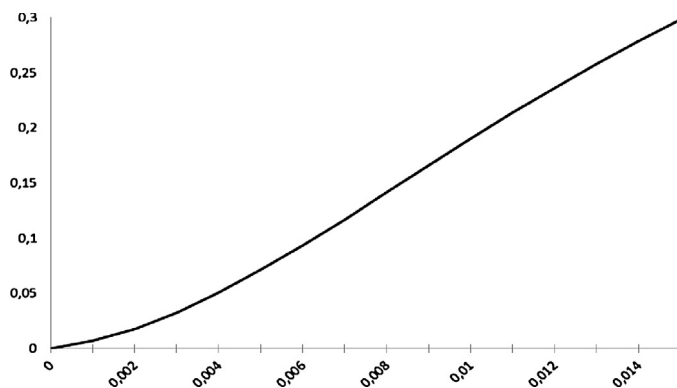


Fig. 2. The “semi-analytical” asset correlation bias as a function of the exchange rate volatility of the US dollar index (USDIX) computed using Eq. (1) with input-parameters estimated from the actual empirical sample. All the parameters are listed in Tables 1 and 2.

second, we study the size and time-variation of the actual bias for the firms and currencies above from the start of the millennium up until early 2013.

4.1. The sensitivity of the asset correlation bias to currency movements

In order to compute the asset correlation bias, estimates of the parameters a and b in Eq. (1) are required, and to estimate these parameters one needs the correlation between each firm’s asset returns and the exchange rate changes plus the volatility of each firm’s asset returns as well as the volatility of the exchange rate changes. The exchange rate changes are easily calculated from observable exchange rates but the asset returns have to be estimated/computed. As described above, in this paper we use one of the most commonly used methods, i.e. the Merton (1974) approach, to estimate asset values, asset returns and asset volatilities/correlations.

In Figs. 2 and 3 the “semi-analytical” asset correlation bias, which is calculated using Eq. (1), is plotted as a function of, respectively, the exchange rate volatility and the asset value–exchange rate correlation (temporarily assuming that both firms’ assets have the same correlation with the exchange rate). We limit ourselves to studying one single currency here, the US dollar index, and all parameters

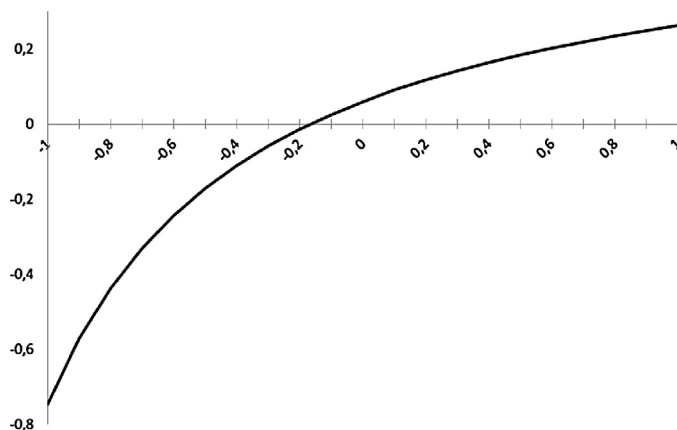


Fig. 3. The “semi-analytical” asset correlation bias as a function of the asset value–exchange rate correlation for the US dollar index (USDIX) computed using Eq. (1) with input-parameters estimated from the actual empirical sample. All the parameters are listed in Tables 1 and 2.

Table 1

Asset value statistics.

Asset volatility (sample volatilities for all 30 firms)	<i>average (cross-sectional)</i>	0.016
	<i>max (cross-sectional)</i>	0.024
	<i>min (cross-sectional)</i>	0.012
Asset correlation (sample correlations for all 435 firm-pairs)	<i>average (cross-sectional)</i>	0.40
	<i>max (cross-sectional)</i>	0.84
	<i>min (cross-sectional)</i>	0.16

are estimated from the actual empirical sample. The parameters can be found in [Tables 1 and 2](#). The first observation is that the bias is an increasing function of both the exchange rate volatility and the asset value–exchange rate correlation. Furthermore, the bias varies significantly and in a non-linear fashion with changes in the volatility and the correlation of the exchange rate. Also, while the bias is positive across the entire spectrum of exchange rate volatilities, the bias, somewhat surprisingly, turns negative for sufficiently negative asset value–exchange rate correlations. This “semi-empirical” analysis indicates that the positive asset correlation bias highlighted by [Tasche \(2007\)](#) and discussed further in [Byström \(2013\)](#) may not always be positive. In fact, we will show empirically that for some of the currencies in this study the bias, indeed, turns negative for shorter periods.

Table 2

Exchange rate statistics.

Exchange rate volatility	US dollar index (USDIX)	<i>full sample</i>	0.0053
		<i>max (250-day window)</i>	0.0086
		<i>min (250-day window)</i>	0.0030
	USD/EUR	<i>full sample</i>	0.0065
		<i>max (250-day window)</i>	0.011
		<i>min (250-day window)</i>	0.0034
	USD/GBP	<i>full sample</i>	0.0060
		<i>max (250-day window)</i>	0.012
		<i>min (250-day window)</i>	0.0038
	USD/YEN	<i>full sample</i>	0.0064
		<i>max (250-day window)</i>	0.010
		<i>min (250-day window)</i>	0.0042
	USD/ARS	<i>full sample</i>	0.012
		<i>max (250-day window)</i>	0.041
		<i>min (250-day window)</i>	0.0004
	USD/CNY	<i>full sample</i>	0.0008
		<i>max (250-day window)</i>	0.0014
		<i>min (250-day window)</i>	0.00001
Asset–exchange rate correlation (average across the 30 firms)	US dollar index (USDIX)	<i>full sample</i>	0.060
		<i>max (250-day window)</i>	0.56
		<i>min (250-day window)</i>	−0.32
	USD/EUR	<i>full sample</i>	0.048
		<i>max (250-day window)</i>	0.45
		<i>min (250-day window)</i>	−0.26
	USD/GBP	<i>full sample</i>	0.072
		<i>max (250-day window)</i>	0.36
		<i>min (250-day window)</i>	−0.20
	USD/YEN	<i>full sample</i>	−0.11
		<i>max (250-day window)</i>	0.072
		<i>min (250-day window)</i>	−0.31
	USD/ARS	<i>full sample</i>	0.008
		<i>max (250-day window)</i>	0.12
		<i>min (250-day window)</i>	−0.09
	USD/CNY	<i>full sample</i>	0.011
		<i>max (250-day window)</i>	0.21
		<i>min (250-day window)</i>	−0.11

Using the sample estimates (average, max and min) in Table 2 as a reference point for empirically representative intervals of exchange rate volatility and average asset value–exchange rate correlation for various currencies, we can compare our semi-analytical results with empirical evidence. The relationships shown in Figs. 2 and 3 are based on the US dollar index, and the average volatility and correlation over the time-period 2000–2013 for the US dollar index are, respectively, 0.0053 and 0.060. As for the time-variation, the empirical exchange rate volatility varies between a low of 0.0030 (in late 2006) and a high of 0.0086 (in late 2008) and the average asset value–exchange rate correlation varies between a low of -0.32 (in late 2002) and a high of 0.56 (in late 2011). With these empirically estimated figures, of which particularly the correlation-interval indicates a very large time-series variation, we can determine which parts of the graphs in Figs. 2 and 3 that are empirically representative as well as get a first rough indication of the actual size (and sign) of the asset correlation bias in the US market.

When it comes to the exchange rate volatility, Fig. 2 shows that for the empirically observed span of volatilities in our data sample the asset correlation bias would vary in a range between 0.03 and 0.17 if all other parameters (hypothetically) were kept constant. More interestingly, for the (average) DJIA-firm asset value–exchange rate correlations, Fig. 3 demonstrates that for the empirically observed (and very wide) span of asset-value–exchange rate correlations the bias of the asset correlation would vary within the range -0.06 to 0.18 if all other parameters were kept constant. That is, the bias would, at times, turn negative (*ceteris paribus*).

Finally, from the semi-analytical relationships presented graphically in Figs. 2 and 3 we can also estimate the sensitivity of the asset correlation bias to changes in either the exchange rate volatility or the asset value–exchange rate correlation. The sensitivities are calculated numerically as the percentage change in the bias (the forward- and backward differences are equal to the second decimal) caused by a $\pm 1\%$ change in the volatility and correlation, respectively, starting at the empirically estimated average values in Table 2 (0.0053 and 0.060, respectively). Our calculations show that for every 1% change (from, say, 0.005300 to 0.0005353 or from 0.005300 to 0.0005247) in the exchange rate volatility (*ceteris paribus*) the asset correlation bias changes $\pm 1.51\%$. In other words, $\Delta_{\text{volatility}} = 1.51$. And for every 1% change in the asset value–exchange rate correlation (*ceteris paribus*) the asset correlation bias changes $\pm 0.23\%$. That is, $\Delta_{\text{correlation}} = 0.23$. From these numbers we learn that the bias is (on average, across the time-period) more sensitive to changes in the volatility of the currency than to changes in the currency's co-variation with the assets. This does not necessarily mean that the volatility is the main driver behind the bias, however. Due to the much larger time-variation in the correlation than in the volatility (the highest asset value–exchange rate correlation in our sample is 800% higher than its sample average while the highest volatility is just 60% above its sample average) the asset value–exchange rate correlation is, nonetheless, most likely the more important determinant of the time-variation in the bias.

4.2. The time-variation in the asset correlation bias

In the analysis above, the semi-analytical relationships between the asset correlation bias and, respectively, the exchange rate volatility and the asset value–exchange rate correlation were studied. Here, we are instead looking at the actual empirical bias when estimating asset correlations amongst the 30 DJIA-firms for six different currency exposures from January 2000 to January 2013. We estimate all the inputs for the bias-calculation, i.e. the volatilities and correlations, on a daily basis using overlapping 250-day long lagged windows.

The average bias (across the 435 correlations) is plotted in Fig. 4 for each of the six currencies, and an immediate observation is that the bias varies significantly across the thirteen year sample period. Moreover, the size of the bias is often significant when compared to the average asset correlation for this sample of firms which is 0.40. At times, the bias is even comparable in magnitude to the (average) asset correlation itself which is a clear indication of an economically relevant bias. At other times, the bias turns negative which is further evidence of the importance of acknowledging the impact of currency fluctuations on asset correlations. The time-variation patterns are different for the different currencies, particularly for the minor ones represented by the Argentine peso (ARS) and the Chinese renminbi (CNY). The ARS represents a currency that has plummeted against the US dollar over the

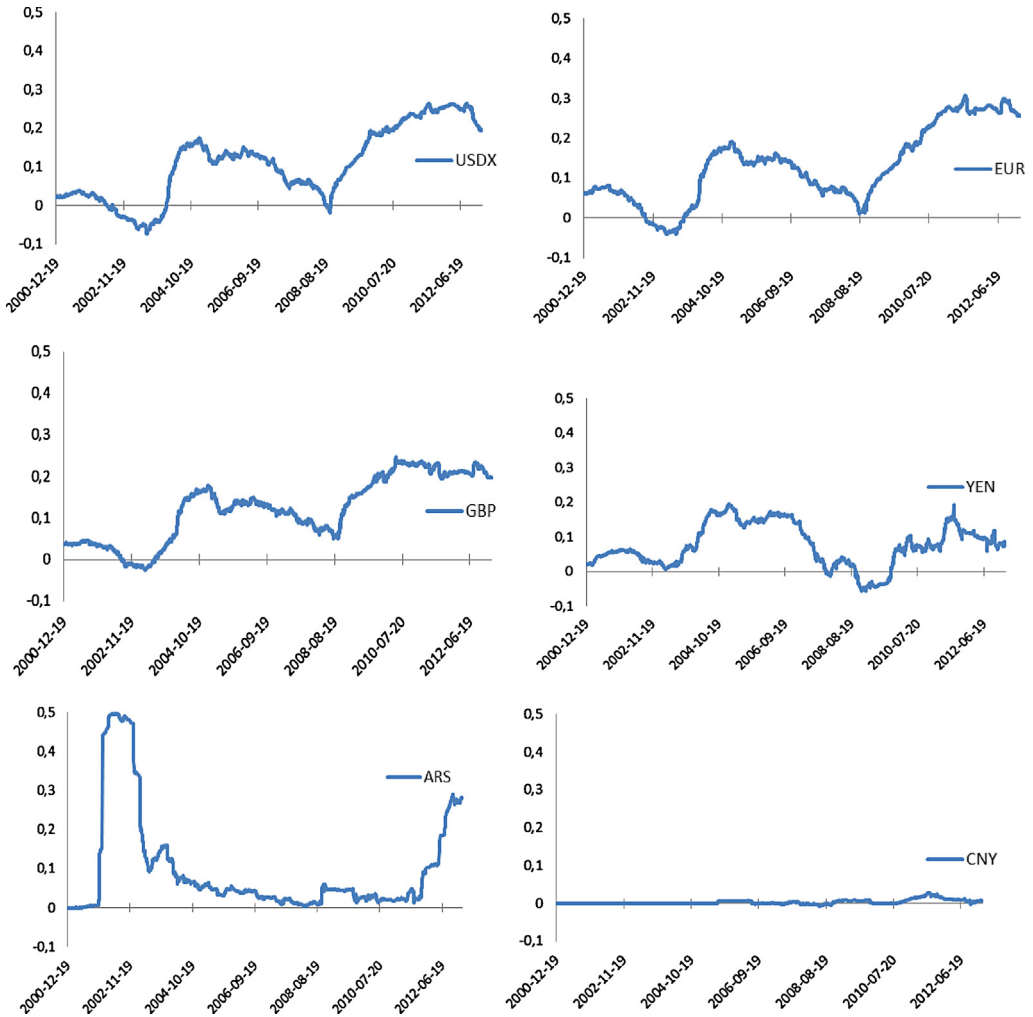


Fig. 4. The average asset correlation bias (for the 435 correlations between the 30 DJIA-firms) across the time-period 2000–2013 for the six currency exposures: the US dollar index (USD), the euro (EUR), the British pound (GBP), the Japanese yen (JPY), the Argentine peso (ARS) and the Chinese renminbi (CNY).

sample period. The credit risk of a portfolio of bonds and loans issued by firms with Argentine peso-exposed assets (and most likely falling market capitalizations) would have had to be adjusted upwards due to the fall in the peso exchange rate and the positive link between the bias and the firms' asset value–exchange rate correlations. An additional (and unrelated) observation is the hike in the bias in 2002 which is caused by the sudden devaluation of the peso in January 2002, the starting point of the following decade-long depreciation. The CNY, in turn, demonstrates the effect of a currency-peg (or quasi-peg) on the bias. From 2000 to 2005 the CNY was effectively pegged to the dollar and there is, consequently, no bias. After the gradual relaxation of the peg in 2005 the bias is no longer zero. The bias is comparatively small, though, since the CNY/USD exchange rate volatility remains very low also after the lifting of the peg.

A final consequence of the bias is that so-called flight-to-quality behavior amongst investors can, indirectly, make the problem with underestimation of credit risk worse, through an underestimation of the asset correlation. During the latter third of the sample, i.e. during the financial crisis, the asset

value–exchange rate correlations for the firms in the DJIA index (not presented) have been significantly higher than before. This is the result of a strengthening of the USD together with a market-wide fall in asset values (and stock prices) which, at least partly, is due to a rotation away from equity into bonds together with US investors repatriating international money and foreign investors re-balancing their portfolios from riskier to safer jurisdictions during the crisis. As an indirect consequence of this behavior, the asset correlation bias increases (as theoretically predicted by Fig. 3 and empirically demonstrated by Fig. 4) and so does the underestimation of the actual portfolio credit risk.

5. Conclusions

Recent findings suggest that the credit risk of corporate debt portfolios is likely to be underestimated due to biased asset correlation estimates when there is a currency mismatch between the firms' assets and liabilities. Tasche (2007) derives analytical expressions for the asset correlation bias and Byström (2013) tests the economic significance of the bias empirically. Here, we continue this work by looking at the time-variation of the bias and on the dependency of the bias on currency movements. Both the volatility of the exchange rate and the correlations between the asset values of the firms and the exchange rate affect the bias, and we find the sensitivity of the bias to the former to be the greatest. The wide fluctuations of the asset value–exchange rate correlations over time, however, mean that these correlations, nonetheless, have a more profound economic significance on the bias. Empirically, the average bias for the cross-section of 30 firms (and 435 asset correlations) in the Dow Jones Industrial Average index has been large for the lion part of the 2000–2013 period although it fluctuates widely. Also, interestingly, and contrary to the assumptions of previous studies, the bias for the average firm-pair has actually been negative for shorter periods. The bias is, of course, more significant for some currencies than for others but the general policy implication is, nonetheless, that the currency exposure of firms in financial institutions' credit portfolios should be acknowledged in risk assessments, at the very least when the institution is stress-tested. Perhaps a rule of thumb in stress tests could be to simply double any traditional asset correlation estimate that ignores exchange rate risk. In times when currency movements are becoming increasingly important such prudence seems more justified than ever.

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